

A Comprehensive Nonlinear Analysis of Electromyogram

Yanli Meng¹ Bingzheng Liu¹ Yuping liu²

¹Department of Physics, Northeast Normal University, Changchun, China, 130022

²The third clinical Hospital, Jilin University, Changchun, China, 130031

Abstract—To test whether electromyogram (EMG) is nonlinear deterministic signal or just random noise, we comprehensively analyze four EMGs of an adult woman. At first, we calculate the correlation time, *L-Z complexity*, approximate entropy (*ApEn*), maximum Lyapunov exponent (Ly_1) and correlation dimension (D_{corr}) of each EMG data and its ten surrogate data. We find that all the results are quite different between each original EMG and its ten surrogate data, i.e. EMG is not a linear random noise, but a nonlinear deterministic signal (though it does not like a low dimensional chaos). EMG is also assessed with recurrence plot analysis (*RPA*), iterated function system (*IFS*) clumpiness test, singular-value decomposition, and Pearson product-moment correlation coefficient (*Pearson's correlation*). All the results of these assessments show that EMG is different from noise. Thus we conclude that EMG is a signal of high dimensional (D_{corr} range from 4 to 6) chaos.

Keywords—EMG, chaos, surrogate data method, D_{corr} , Ly_1 , *ApEn*

I. INTRODUCTION

As the use of EMG is very convenient and fast, it is now becoming increasingly a powerful measure to get information and to diagnose about the muscular and nervous systems [1,2]. For example, it can diagnose some causes of muscle weakness or paralysis, muscle or motor problem (e.g. involuntary muscle twitching and nerve damage or injury). But up to now, most methods of EMG are still based on linear and statistical analysis. Only a few people dealt with nonlinear principle and method. So far as our opinion, most physiological processes are nonlinear, most probably so does EMG. Therefore we think in the study of EMG, it is important to know whether EMG is nonlinear in its character or not. In the past two decades, some people examined it, but the methods they used were all too simple to draw convincing conclusion. In this paper, we use a fairly comprehensive nonlinear dynamical analysis of 4 EMG data of an adult woman. Synthesizing all of our results and analysis, we can conclude that EMG obeys nonlinear deterministic law. It is probably chaos with D_{corr} greater than 4 and smaller than 6.

II. METHODS

A. Data acquisition

We take four EMG data from the same subject, which are sampled respectively from left back and right back before and after therapy (an active exercise). Sampling frequency is 1000Hz. The length of each data is 10000 points in our

analysis (all the actually measured data length are much greater than this). Fig. 1 is the EMG of left back before therapy. The others are similar to this one.

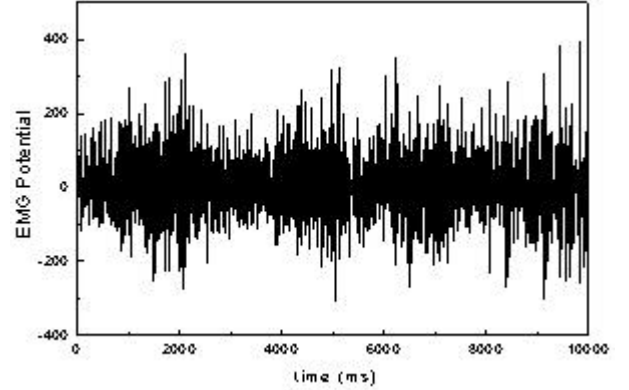


Fig. 1. An EMG signal, the ordinate is in an arbitrary unit

B. D_{corr} and Ly_1

We reconstruct phase space for each EMG data with time delay τ equal to the measured correlation time (because the appropriate reconstruction of phase space is not very sensitive to the value of τ , it is sufficient accurate for such a choice), embedding dimension (D_{emb}) goes from 2 to 10, then calculate D_{corr} and Ly_1 for each D_{emb} , and plot the $D_{corr} - D_{emb}$ curve.

C. *ApEn*

ApEn is a recently introduced characteristic quantity for quantifying regularity or complexity, which facilitate the analysis of noisy and short (even as short as 100 points) data, and is robust to outliers, so it is very suitable for the analysis of biological signals [3,4]. In *ApEn* (m, r), the parameter m is the length of compared runs, and r is effectively a filter. When we compare *ApEn* (m, r)(A) with *ApEn* (n, s)(B) for two different systems A and B, We must take $m = n$ and $r = s$, otherwise the result is without meaning.

D. Method of surrogate data

The essential of this method is as follows [5]:

a. For a given original data, construct a set of random data (called the “surrogate data”). Each of the surrogate data is obtained just by shuffling the order of the original data. So all the surrogate data have the same statistical properties

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(probability distribution, mean value and standard deviation, et al.) as the original data. (Another common method for obtaining surrogate data is to shuffle the phases of the Fourier components of the power spectrum of the original data. In this way the surrogate data has the same power spectrum and correlation function as the original data).

If the original data and its surrogate data differ significantly, then the original data under studying is not a linear stochastic signal, i.e. it represents a nonlinear deterministic process. If there is no significant difference between the original data and surrogate data set, this means that the original data also represents a linear stochastic process.

b. For practical test for nonlinearity, choose certain characteristic quantity Q (e.g. D_{corr} , Ly_1 , complexity and $ApEn$, et al.), calculate Q for both the original data and its surrogate data. Define the **Significance of difference** as:

$$S = | \langle Q_{surr} \rangle - Q_{orig} | / SD \quad (1)$$

where Q_{orig} is the value of Q for the original data, $\langle Q_{surr} \rangle$ and SD denote respectively the mean and standard deviation of the surrogate data set.

Criterion:

1) If $S \geq 2.0$, the original data obeys a certain nonlinear deterministic law, and it is probably chaos (of course, we have to also examine the values of D_{corr} , Ly_1 , et al.).

2) If $S < 2.0$, the original data is a linear process, i.e. it does not obey any nonlinear deterministic law.

III. RESULTS

A. D_{corr} , Ly_1 and correlation time

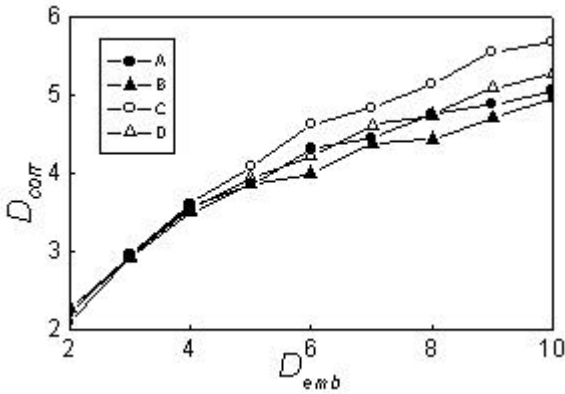


Fig. 2. Change of D_{corr} with embedding dimension (D_{emb}) of the four EMGs, which respectively corresponding to left back before therapy (A), left back after therapy (B), right back before therapy (C) and right back after therapy (D) for the same subject

The results for D_{corr} are shown in Fig 2. We see $D_{corr} - D_{emb}$ curves are all without saturated horizontal plateau. This is caused by effect of noise component in the data. Thus we cannot simply determine D_{corr} by these curves. For the sake of determining best embedding and correct D_{corr} value, we

also use the method of false nearest neighbors and the method of singular value decomposition (Fig. 5. B) [6,7]. Both these two methods show that the correct D_{emb} is in the range of 6 to 8. Thus from Fig.2, we see the four corresponding D_{corr} are greater than 4 and smaller than 6.

Calculated Ly_1 of the four EMG are 0.217, 0.216, 0.208, 0.227 (with $D_{emb} = 7$). They are greater than zero.

The Correlation times are 1.941, 2.183, 1.845, 1.901 respectively, while that of the stochastic signal is usually smaller than 1.

These results all support EMG being a nonlinear chaos.

B. $ApEn$

$ApEn$ values of the four EMGs are 1.252, 1.211, 1.345 and 1.295 respectively, whereas that of a measured stochastic noise is 1.636. We can see there is no significant distinction among the four original $ApEn$ values, whereas they are obviously different from that of noise. This shows the complexity of EMG is less than noise, i.e. EMG is more regular than noise.

C. Method of surrogate data

a. Graph of D_{corr}

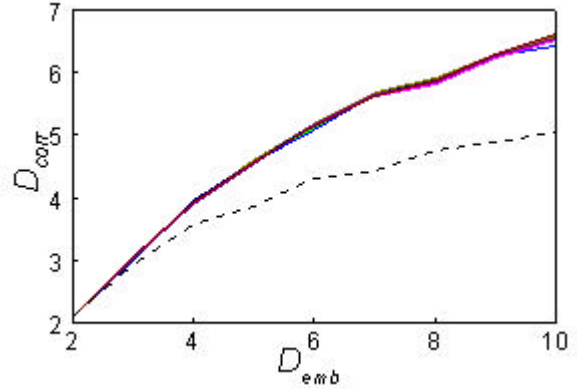


Fig. 3. $D_{corr} - D_{emb}$ curves of the original data (dash line) and the ten surrogate data (solid lines).

Fig.3 is a set of typical measured $D_{corr} - D_{emb}$ curves. We see the original $D_{corr} - D_{emb}$ curves are far from the corresponding tolerance band of the set of surrogate data. This means that EMG is not linear stochastic data, but is signal (contaminated with noise) obeying nonlinear deterministic law. The results of the three remainder EMGs are similar.

b. Significance of difference

Take $ApEn$ and $L-Z$ complexity as characteristic quantity Q and calculate their significances of difference separately:

1) Values of $\langle ApEn \rangle$ and SD of the four set of ten surrogate data are 1.623, 1.621, 1.623, 1.619 and 0.0124,

0.0168, 0.0233, 0.0197 respectively. Thus from (1), S values are 29.9, 24.4, 11.9 and 16.4 respectively. They are much greater than 2.

2) Calculation of $L-Z$ complexity is similar to that of $ApEn$, $L-Z$ complexities of the four original EMG data are 0.751, 0.710, 0.748 and 0.765. While the mean values of the four set of surrogate data are 1.029, 1.031, 1.028, 1.029 ($L-Z$ complexity of white noise is equal to 1.0 by definition), and the SD values are 0.0668, 0.0043, 0.0056, 0.0044. Thus the S values are 41.6, 74.7, 50.0 and 60.0. These are all much greater than 2.

From these S values for $ApEn$ and $L-Z$ complexity and the criterion, we may conclude that EMG is not linear noise signal, but obeys a certain nonlinear deterministic law.

D. RPA

Recurrence plot is a useful tool to identify whether there is some deterministic law in the data [8]. It is particularly useful in dealing with non-stationary data. The recurrence plot is an array of dots with $x(i)$ as both abscissa and ordinate ($i=1, \dots, N$) (where N is the length of data) in $N \times N$ square. For random data, the obtained plot will be completely disorder and uniform; whereas if there exists deterministic fact in the data, the plot will have some recurrent points which form some diagonal line segments of different lengths.

Fig. 4 is the recurrence plot of one EMG data. We see there are many short lines parallel to the diagonal. So it is also an evidence of deterministic structure of EMG.



Fig. 4. Recurrence plot of the EMG signal

E. Complementary methods

We also use some additional methods to conform the above assertion. These are:

a. Singular value decomposition

This method is based on the analysis of the eigenvalues of the correlation matrix sorted from largest to smallest versus

the order of matrix (M). The number of significant eigenvalues, like the correlation dimension, is a measure of the complexity of the system. For pure deterministic signal, the eigenvalue curve will fall abruptly to zero at the value of M equal to the correct D_{emb} . For noise, the eigenvalues are all very large and the curve does not fall obviously (Fig. 5. A). Fig. 5. B is a curve for one EMG data. We see even though the EMG data is contaminated with noise, but it is a deterministic signal with a large Signal-to-Noise ratio, the correct D_{emb} is about 6-8.

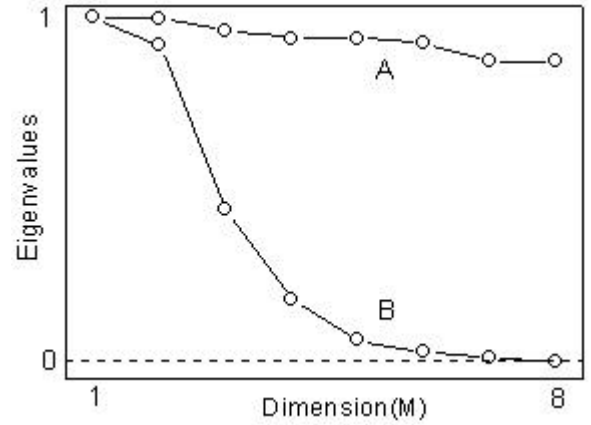


Fig. 5. Eigenvalues of the correlation matrix for a noise (A) and an EMG (B).

b. IFS clumpiness test

Divide the range of data into 4 quartiles [9]. Random data (white noise) fills the square uniformly, while colored noise and chaotic data produce pattern or clumps. The eye is very sensitive to these patterns of this sort.

Figure 6 is such a pattern of one EMG, we see it is obviously different from uniform (noise) but has some structure, i.e. EMG is evidently different from stochastic noise.

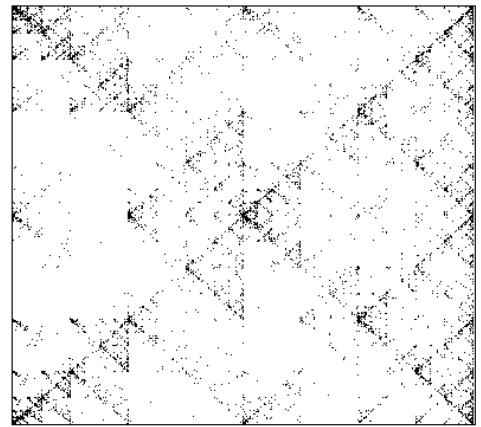


Fig.6 IFS clumpiness test of one EMG

c. Pearson's correlation

This is a measure of how strongly each data point correlates with its immediate predecessor [10]. It ranges from +1 (perfect correlation) to -1 (perfect anticorrelation) with 0 representing white noise.

Our results are 0.765, 0.794, 0.753, 0.752, so EMG is quite different from noise and has strong positive correlation.

IV. CONCLUSION

Synthesize all the above results and analysis, we can draw the conclusion that EMG obeys a certain nonlinear deterministic law and its D_{corr} value is greater than 4 and smaller than 6, namely, it is probably a high dimensional chaos.

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